

fortiss

fortiss fields of research



Chair of Software Engineering for Data-intensive Applications



Architectures and Services for Critical Infrastructures

Simple design and clear modeling for
software simulation and integration



Automated Software Testing

Software Engineering
for data intensive applications



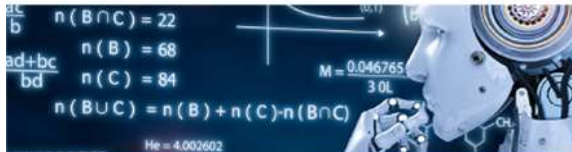
Human-centered Engineering

Understand and explain decisions of
intelligent systems from the user's point of
view



Industrial Internet of Things

Enabling the next generation
of IIoT applications and services



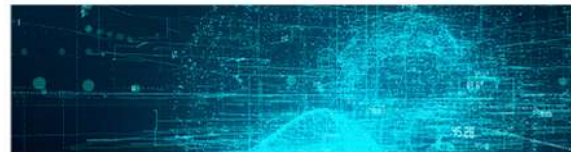
Machine Learning

Development of solutions
involving data and knowledge



Model-based Systems Engineering

Solutions for flexible engineering of cyber-
physical systems



Neuromorphic Computing

Artificial intelligence: the third
generation of neural networks



Platform Engineering

Pervasive, robust and trustworthy platforms



Requirements Engineering

Efficiently deal with volatile and
heterogeneous requirements



Safety and Security

Guaranteeing secure systems
in software and system development



Software Dependability

Rigorous validation and verification
for dependable and safe software systems



Automated Software Testing

We like to generate tests, monitor them, and make them real!



Dr. Andrea Stocco
Head of AST @ fortiss
Prof. @ TUM

stocco@fortiss.org

andrea.stocco@tum.de



Stefano Carlo Lambertenghi
Generative AI Testing /
Reality Gap Assessment and
Mitigation

lambertenghi@fortiss.org



Oliver Weiß
Algorithm Optimization
(co-supervised
w/ S. Kacianka)

weissl@fortiss.org



Lev Sorokin
Algorithm
Optimization /
Cross-Simulation
Testing

sorokin@fortiss.org



Xingcheng Chen
eXplainable Artificial
Intelligence (XAI) /
Post-Production Testing

xchen@fortiss.org



Davide Yi Xian Hu
Generative AI Testing
(visiting)

hu@fortiss.org

Automated Software Testing

Main domain areas

- **Traditional Software Systems**

- Search-based Test Generation
- Regression Testing (e.g., test prioritization, test minimization)

- **Web Applications**

- End-to-End GUI Testing
- Test Maintenance
- Test Robustness
- Automated Crawling

- **Deep Learning Systems**

- Test Generation (search-based, model-based, generative AI)
- Failure Prediction (black-box, white-box)
- Debugging (explainable AI, uncertainty quantification)

- **Cyber Physical Systems**

- Deep learning or Reinforcement learning
- Reality Gap Assessment and Mitigation
- Automotive, UAVs, Elevators



Automated Software Testing

Main domain areas

- **Traditional Software Systems**

- Search-based Test Generation
- Regression Testing (e.g., test prioritization, test minimization)

- **Web Applications**

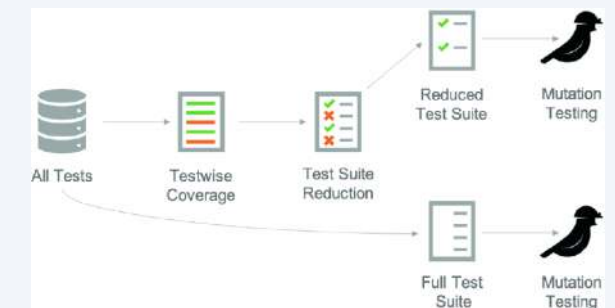
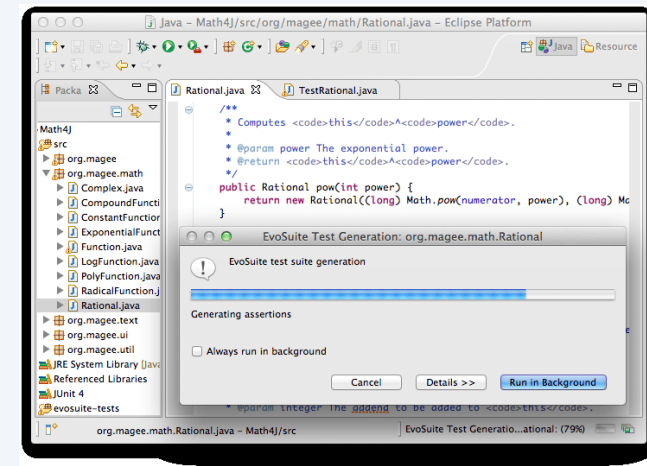
- End-to-End GUI Testing
- Test Maintenance
- Test Robustness
- Automated Crawling

- **Deep Learning Systems**

- Test Generation (search-based, model-based, generative AI)
- Failure Prediction (black-box, white-box)
- Debugging (explainable AI, uncertainty quantification)

- **Cyber Physical Systems**

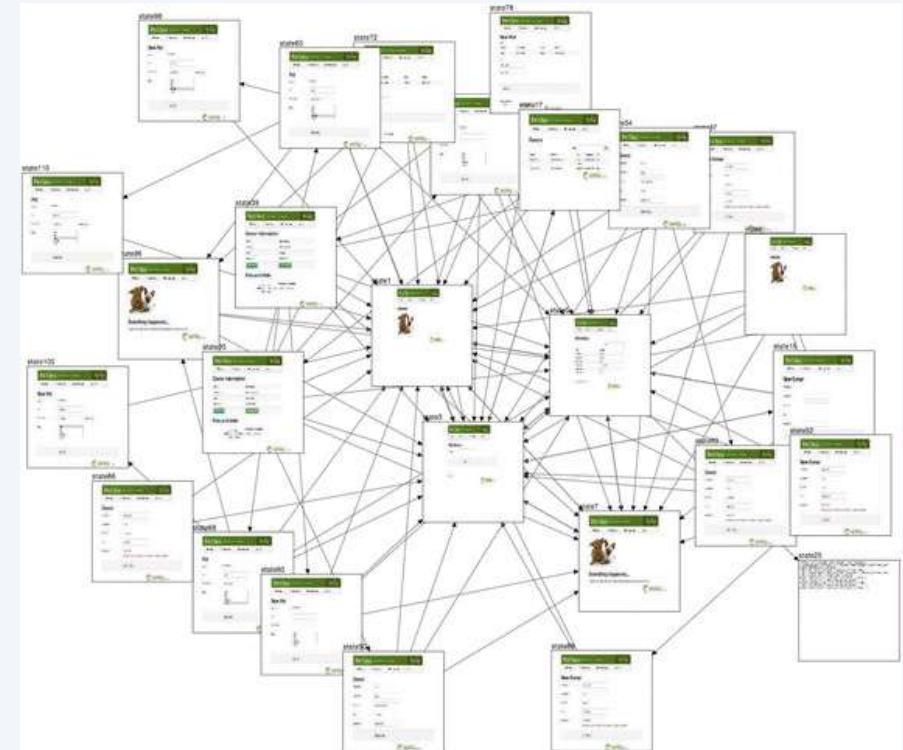
- Deep learning or Reinforcement learning
- Reality Gap Assessment and Mitigation
- Automotive, UAVs, Elevators



Automated Software Testing

Main domain areas

- **Traditional Software Systems**
 - Search-based Test Generation
 - Regression Testing (e.g., test prioritization, test minimization)
- **Web Applications**
 - End-to-End GUI Testing
 - Test Maintenance and Repair
 - Test Robustness
 - Automated Crawling
- **Deep Learning Systems**
 - Test Generation (search-based, model-based, generative AI)
 - Failure Prediction (black-box, white-box)
 - Debugging (explainable AI, uncertainty quantification)
- **Cyber Physical Systems**
 - Deep learning or Reinforcement learning
 - Reality Gap Assessment and Mitigation
 - Automotive, UAVs, Elevators



Automated Software Testing

Main domain areas

- **Traditional Software Systems**

- Search-based Test Generation
- Regression Testing (e.g., test prioritization, test minimization)

- **Web Applications**

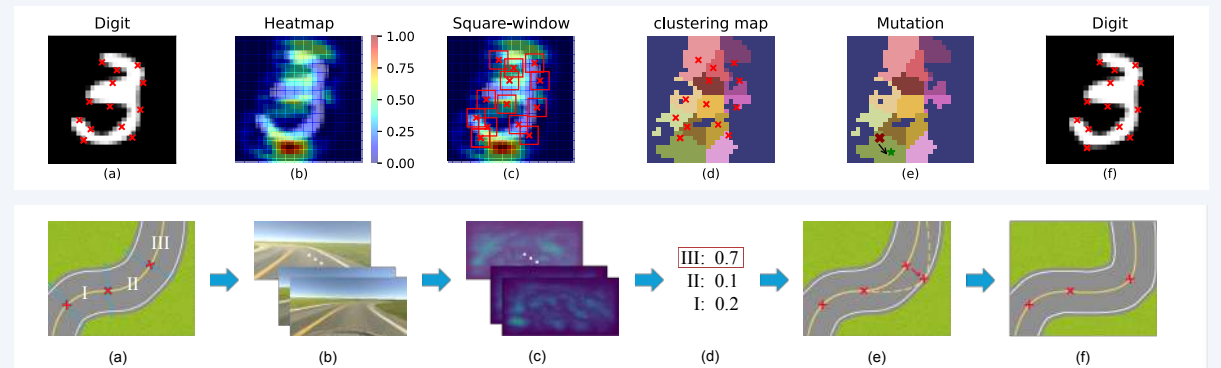
- End-to-End GUI Testing
- Test Maintenance
- Test Robustness
- Automated Crawling

- **Deep Learning Systems**

- Test Generation (search-based, model-based, generative AI)
- Failure Prediction (black-box, white-box)
- Debugging (explainable AI, uncertainty quantification)

- **Cyber Physical Systems**

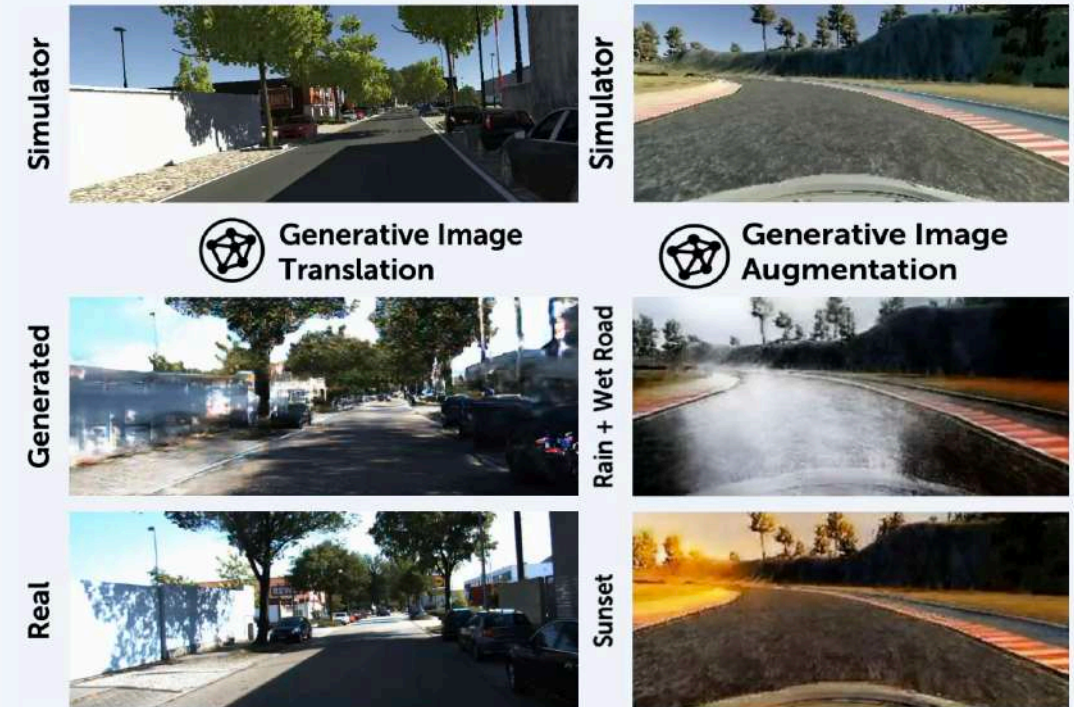
- Deep learning or Reinforcement learning
- Reality Gap Assessment and Mitigation
- Automotive, UAVs, Elevators



Automated Software Testing

Main domain areas

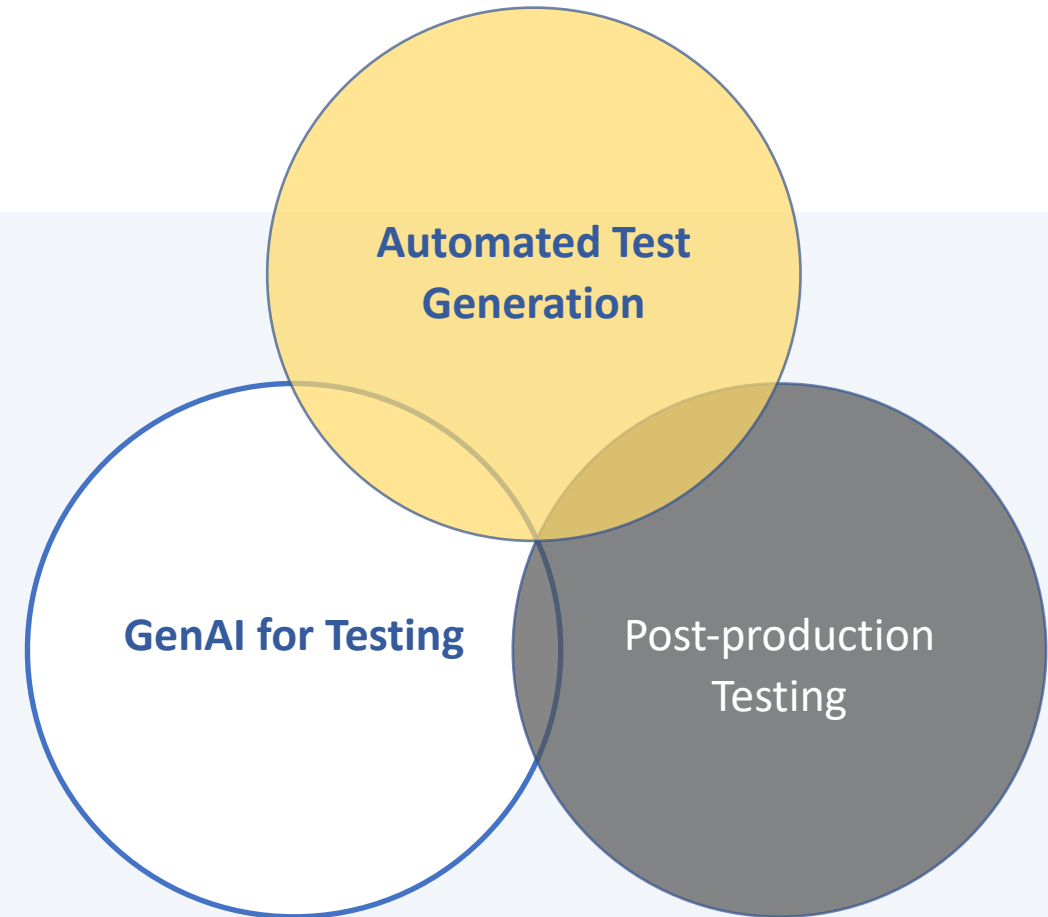
- **Traditional Software Systems**
 - Search-based Test Generation
 - Regression Testing (e.g., test prioritization, test minimization)
- **Web Applications**
 - End-to-End GUI Testing
 - Test Maintenance
 - Test Robustness
 - Automated Crawling
- **Deep Learning Systems**
 - Test Generation (search-based, model-based, generative AI)
 - Failure Prediction (black-box, white-box)
 - Debugging (explainable AI, uncertainty quantification)
- **Cyber Physical Systems**
 - Deep learning or Reinforcement learning
 - Reality Gap Assessment and Mitigation
 - Automotive, UAVs, Elevators



Automated Software Testing

Main research topics

- **Automated Test Generation**
How can we automatically generate complex scenario-based tests efficiently and effectively?
- **GenAI for Testing**
How can we leverage generative adversarial techniques, uncertainty quantification and conformal predictions, explainable AI for testing CPS
- **Post-production Testing**
How to ensure a high dependability of deep neural network driven-cyber-physical systems (CPS) in production?



Automated Software Testing

Search-based Evolutionary Algorithms



ADS & ADAS

- End-to end DNNs (level 2)
- Full AD stacks



Critical Test Scenarios Identification



High fidelity sim-based Validation



<https://git.fortiss.org/opensbt>

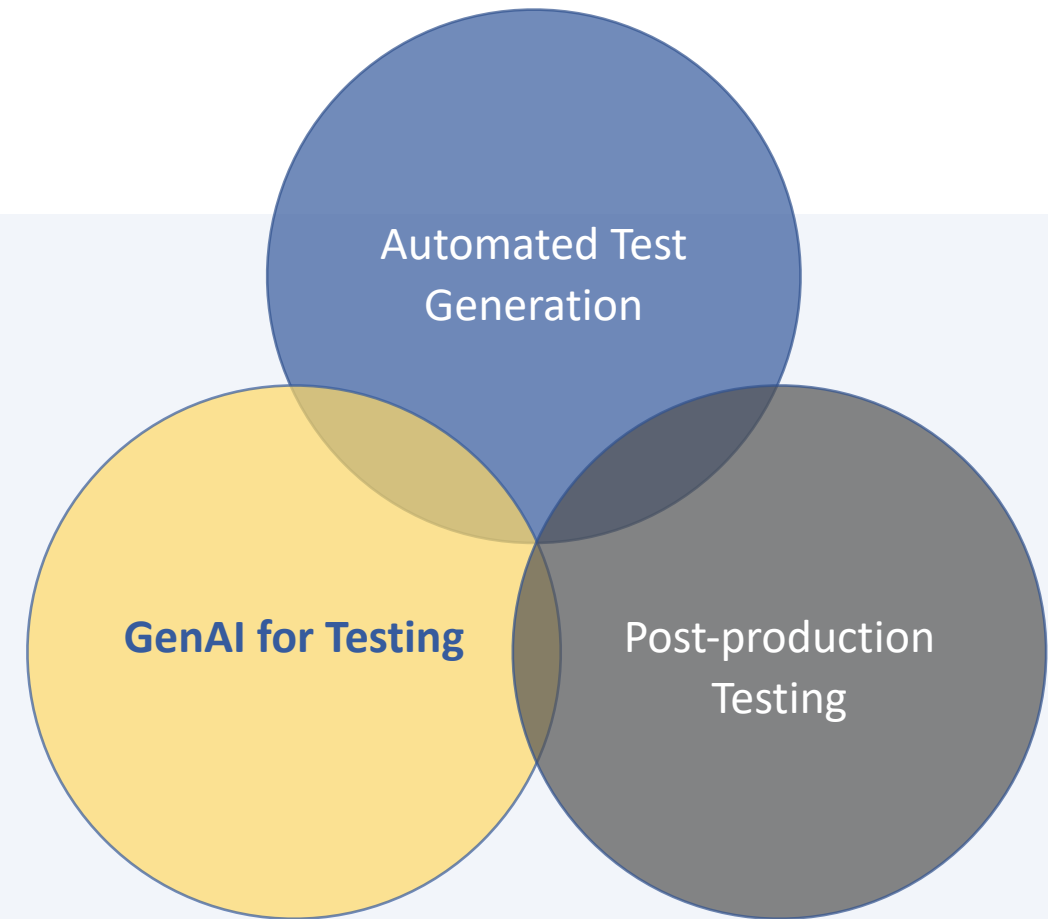


Sorokin et al. OpenSBT: A Modular Framework for Search-based Testing of Automated Driving Systems. In Proceedings of ICSE Workshops 2024.

Automated Software Testing

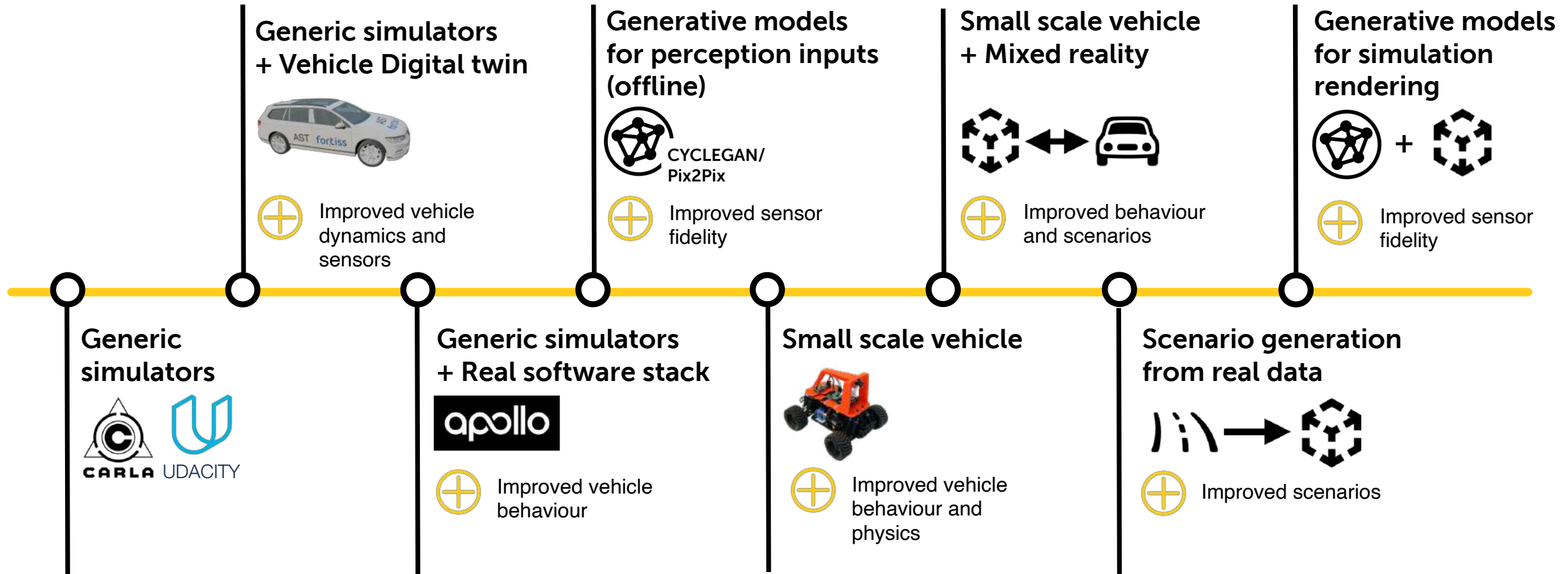
Main research topics

- **Automated Test Generation**
How can we automatically generate complex scenario-based tests efficiently and effectively?
- **GenAI for Testing**
How can we leverage generative adversarial techniques, uncertainty quantification and conformal predictions, explainable AI for testing CPS
- **Post-production Testing**
How to ensure a high dependability of deep neural network driven-cyber-physical systems (CPS) in production?



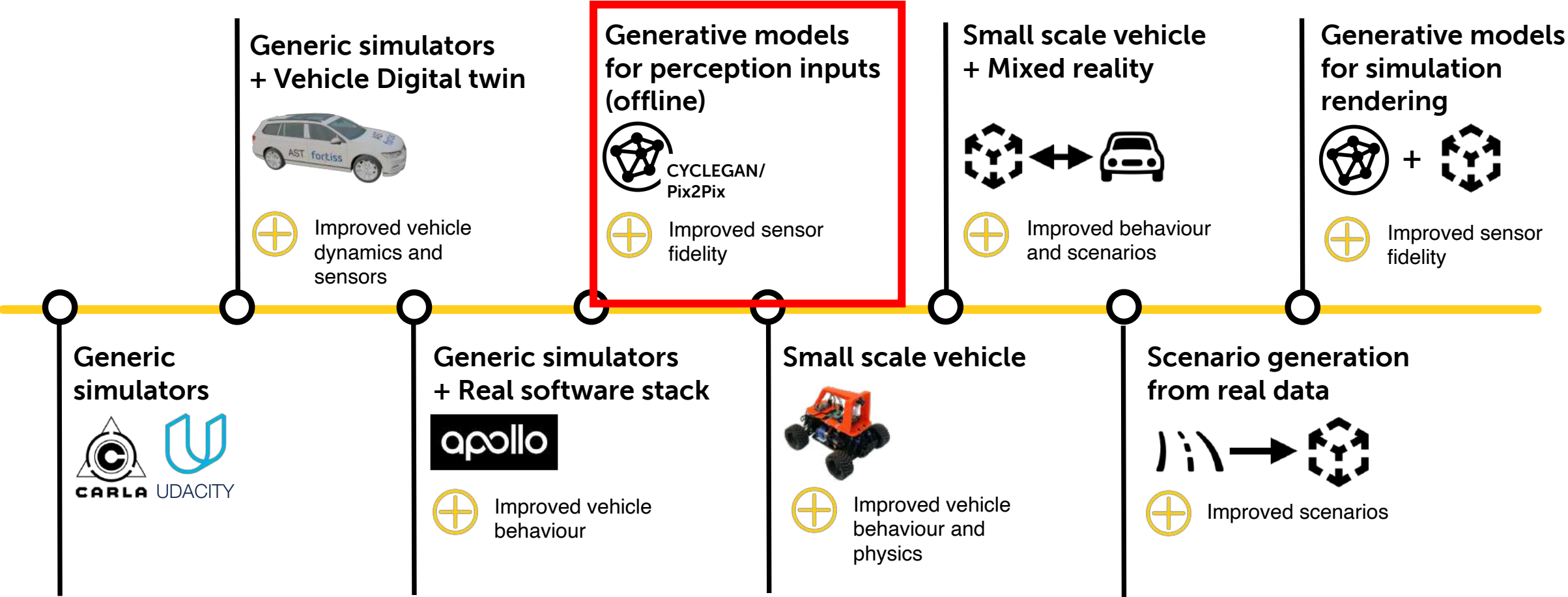
Reality Gap

Our mitigation and evaluation techniques



Reality Gap

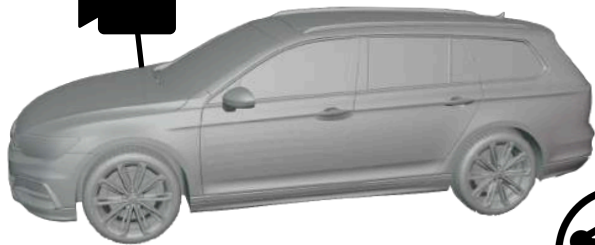
Our mitigation and evaluation techniques



Perception Reality Gap

Difference between simulated and real input images

Simulation



**Simulated
Behaviour**

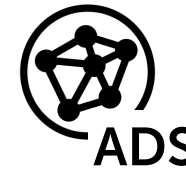
Gaidon, A et al.
Geiger, A et al.

2016
2013

Perception Gap



Real-world



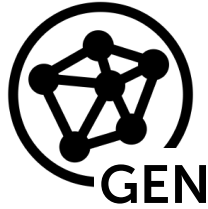
**Real
Behaviour**

\neq

Generative Image-to-Image Translation

Generative models for perception reality gap mitigation

Simulation

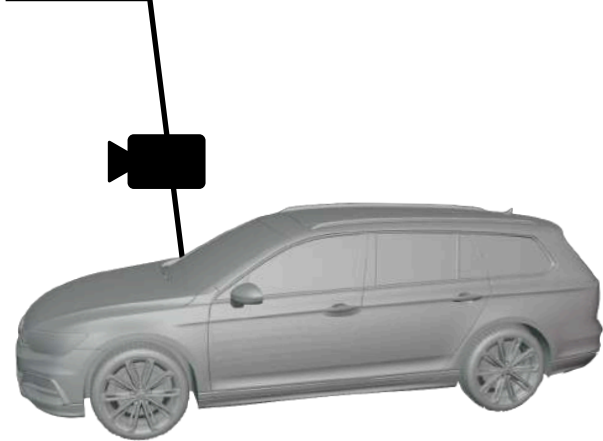


Generated

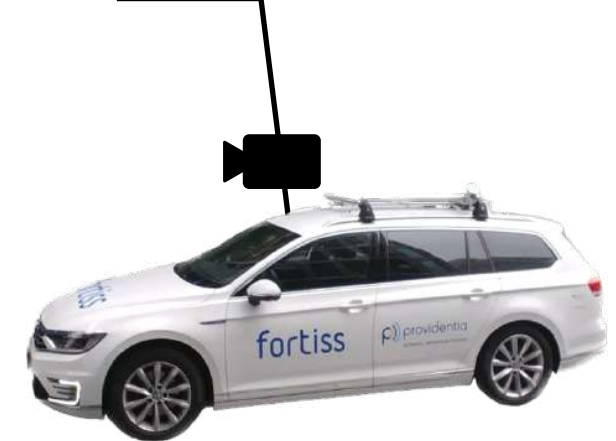


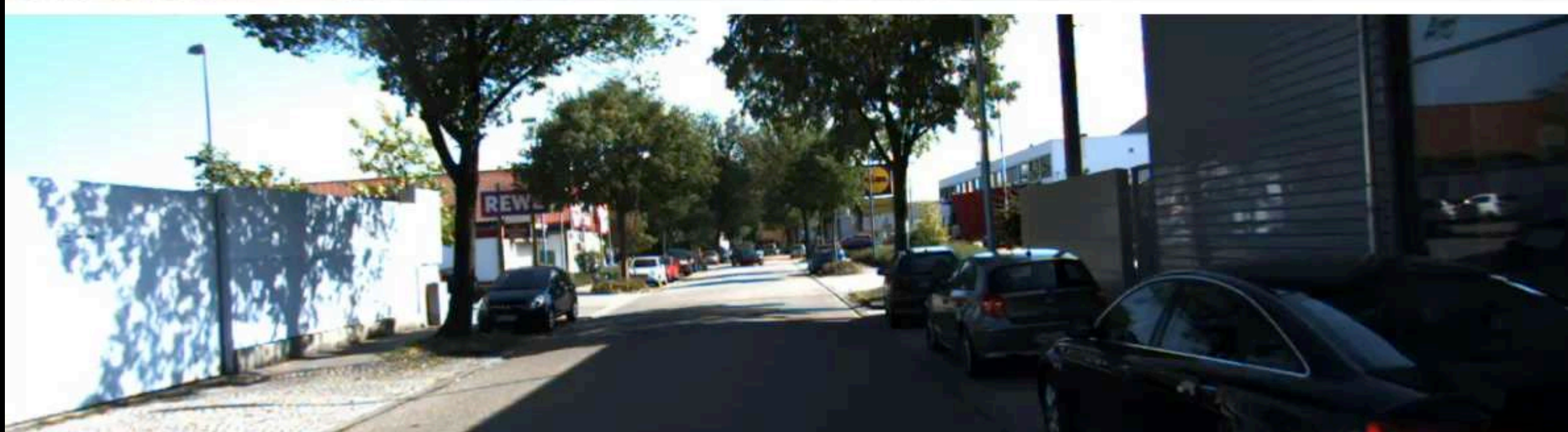
~

Real-world



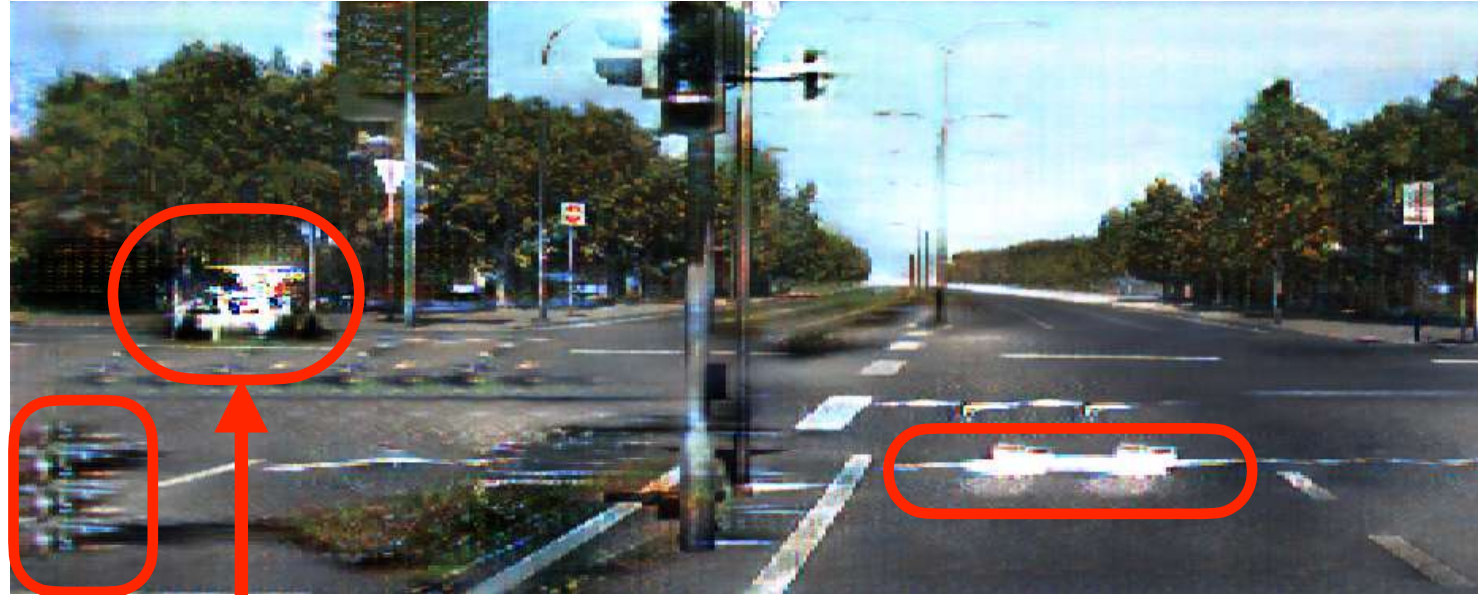
Mitigate Gap





Generative Image-to-Image Translation shortcomings

Generated



Real-world



Methodology



Image Quality Metrics



Distribution Level Metrics

IS
FID
KID

Inception-score
Fréchet Inception Distance
Kernel Inception Distance



Single Image Metrics

SSIM
PSNR
MSE
CS
TSI
WD
KL
Histl
CPL
SSS

Structural Similarity Index
Peak signal-to-noise ratio
Mean Squared Error
Cosine Similarity
Texture Similarity Index
Wasserstein Score
KL Divergence
Histogram Intersection
Classifier Perceptual Loss
Semantic Segmentation Score

Borji, A. et al.
Pang, Y. et al.

2018
2022

Empirical evaluation



Correlation

How do existing Image-to-image evaluation metrics correlate with the associated ADS behaviour?

Takeaways



I

REAL



Relative
Behaviour
Metrics



Image
Metrics

1

Image-to-image GenAI tools effectively tackle domain adaptation in ADS

2

Current GenAI metrics don't align well with the software behavior that relies on their output

3

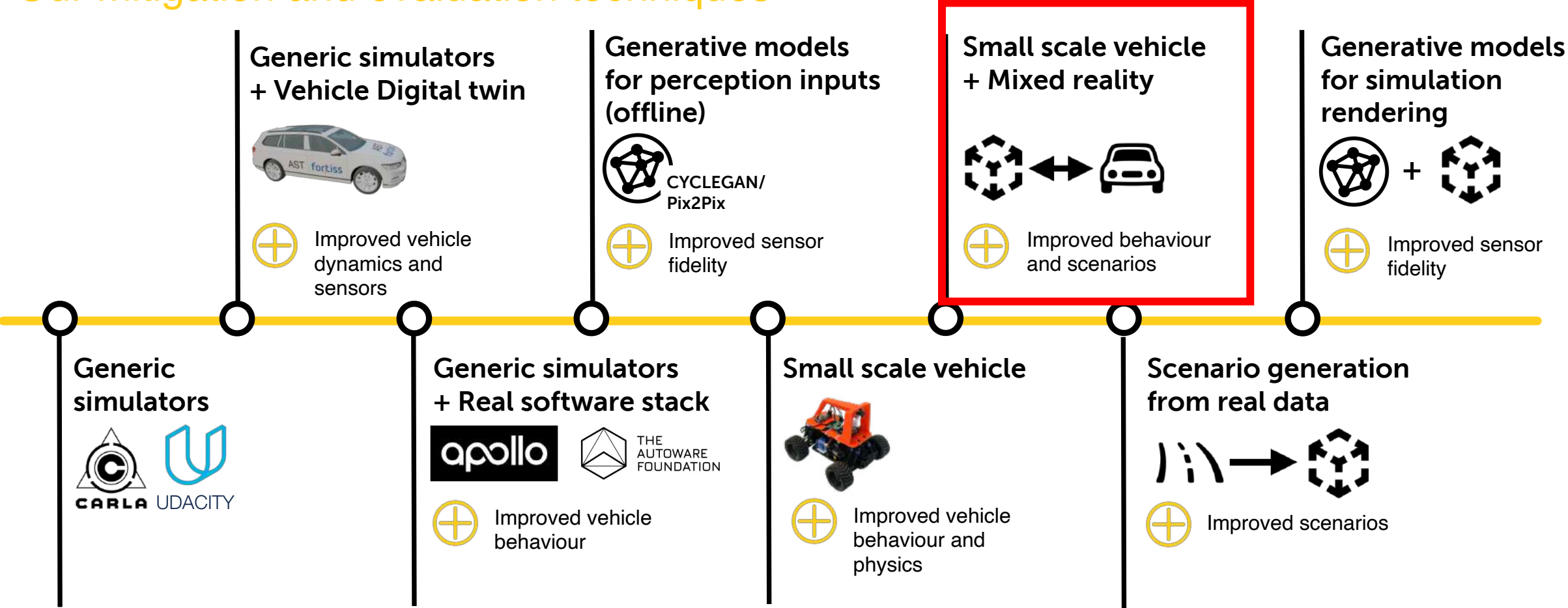
We need more domain-informed, semantic-aware metrics

Lambertenghi and Stocco.

Assessing Quality Metrics for Neural Reality Gap Input Mitigation in Autonomous Driving Testing
17th IEEE International Conference on Software Testing, Verification and Validation (ICST) 2024

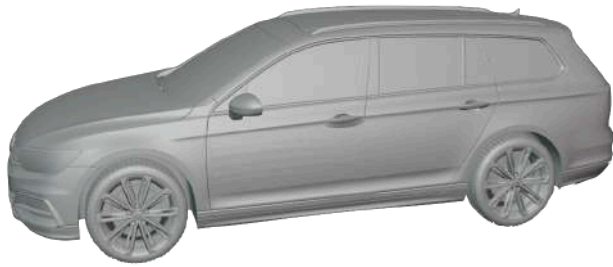
Reality Gap

Our mitigation and evaluation techniques



Gap mitigation

Simulation testing



Simulated

Behaviour
Scenarios
Sensors

Small-scale Real-world testing



Real

Behaviour
Sensors

Full-scale Real-world testing

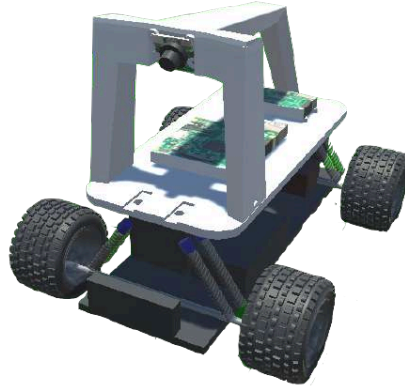


Real

Behaviour
Scenarios
Sensors

Gap mitigation

Simulation
testing



+

Real-world
testing



=

Mixed-reality

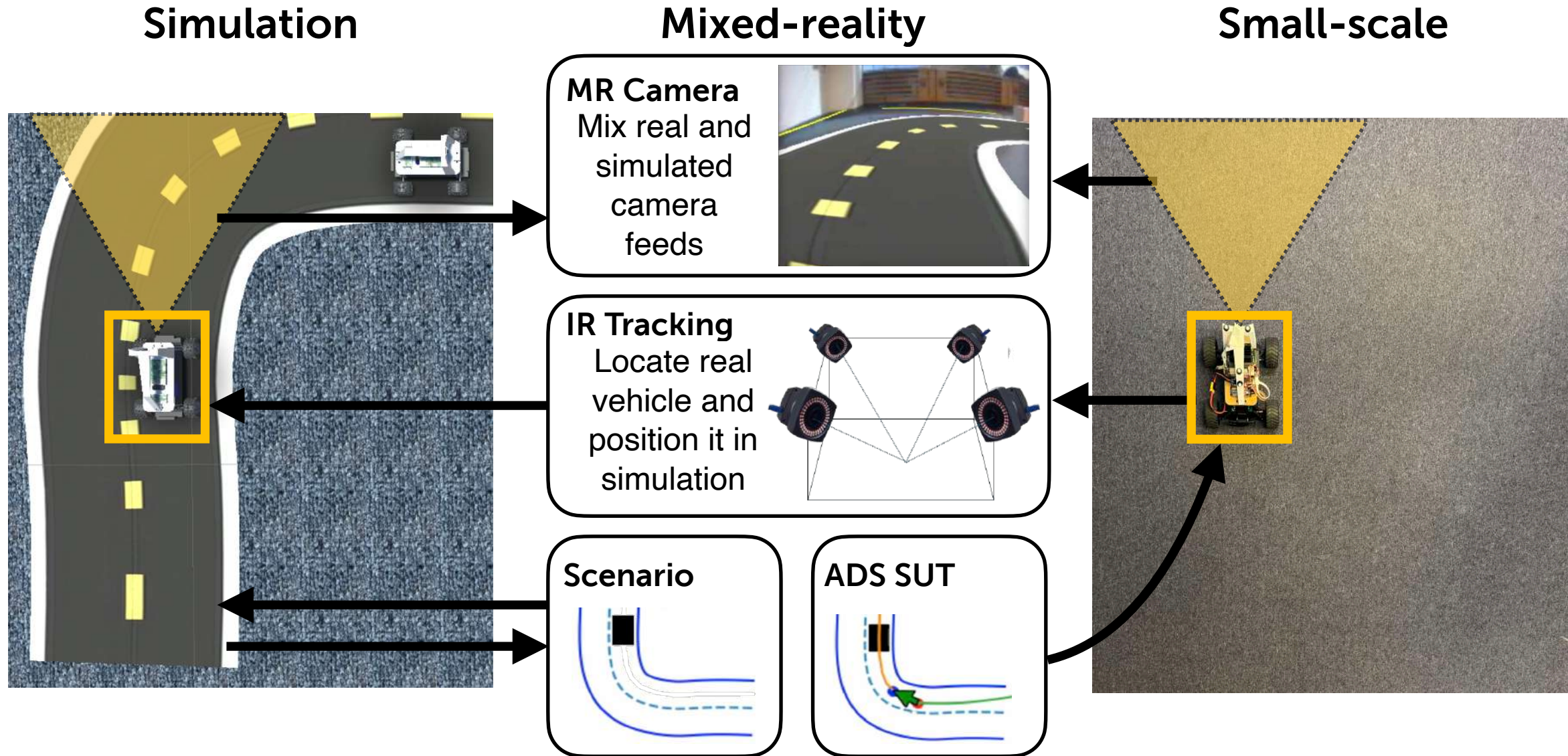


More realistic than sim



More versatile than full-scale

Mixed-reality framework

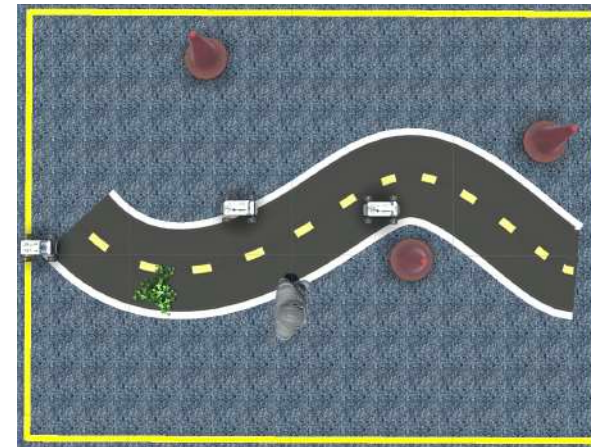
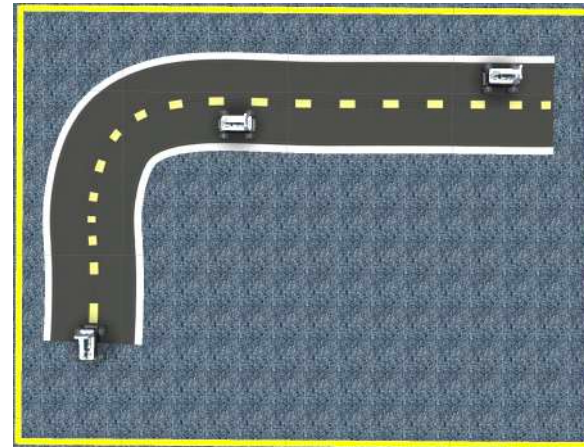
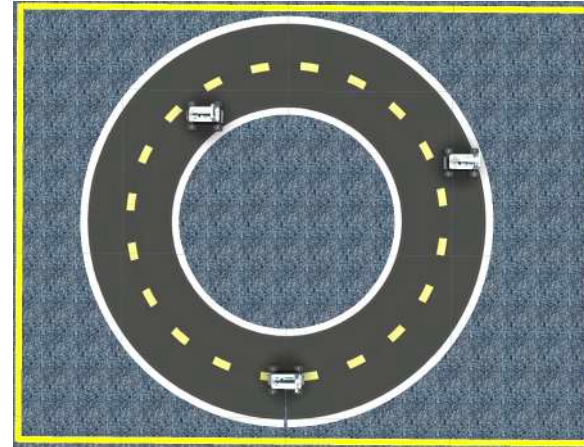
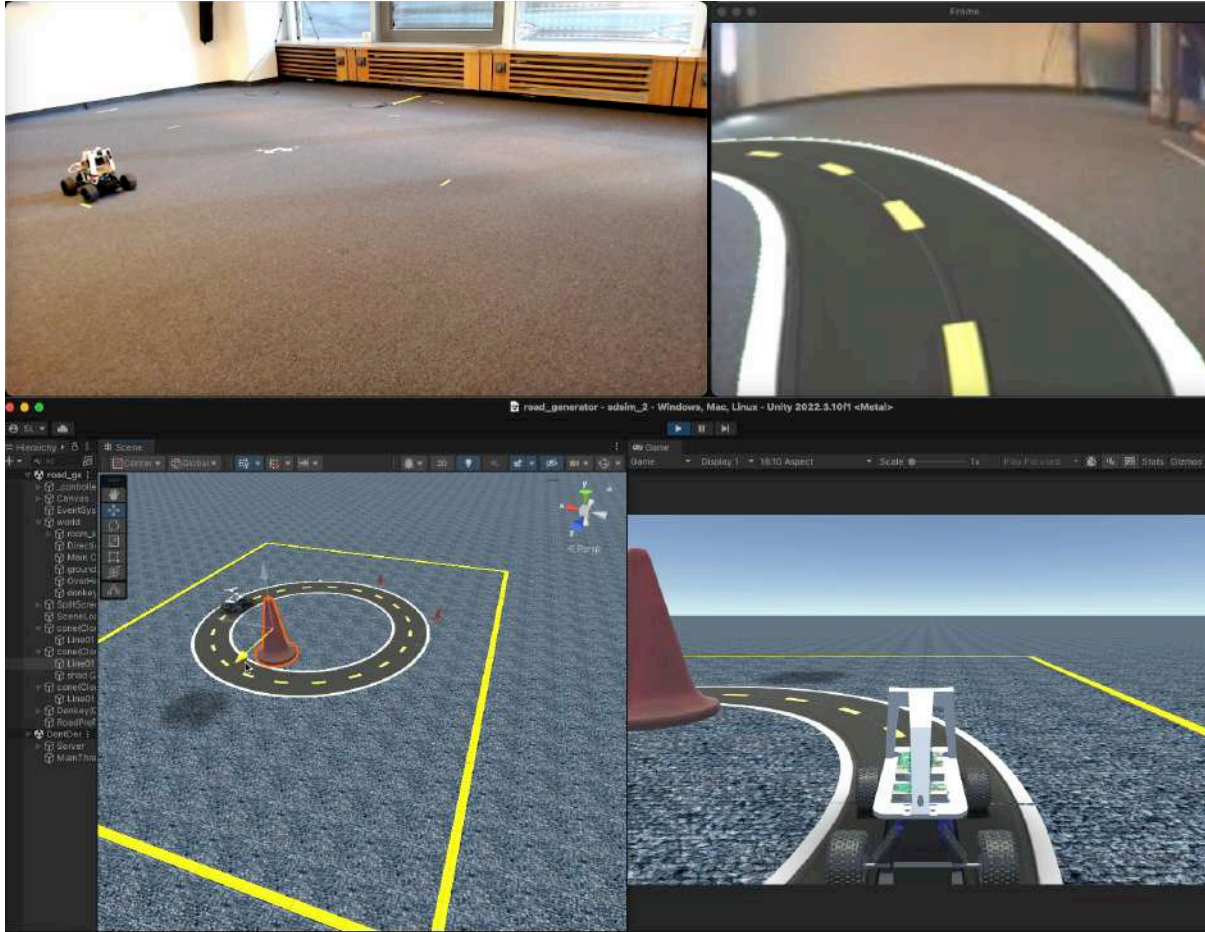


Mixed-reality testing framework

- Test complex scenarios
- Track obstacles in real-time
- End-to-end ADS testing
- Full-stack ADS testing

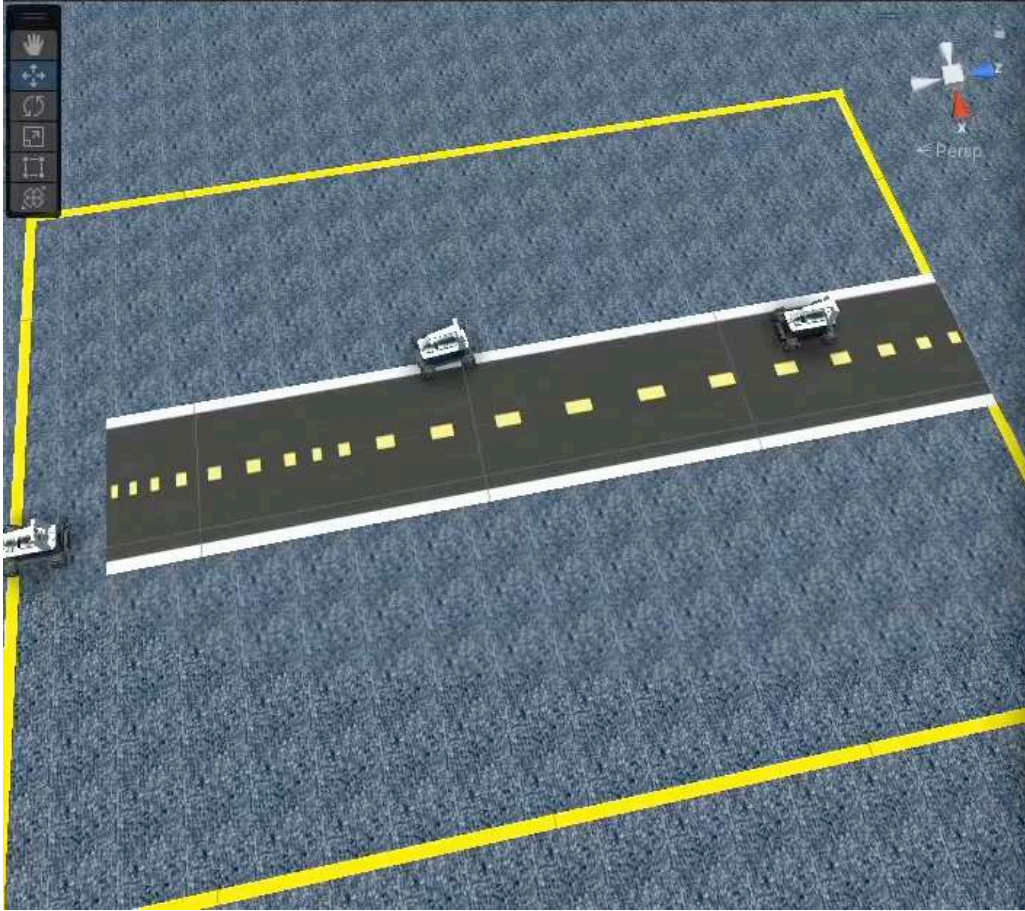
Mixed-reality framework

○ Test complex scenarios



Mixed-reality framework

○ Track obstacles in real-time

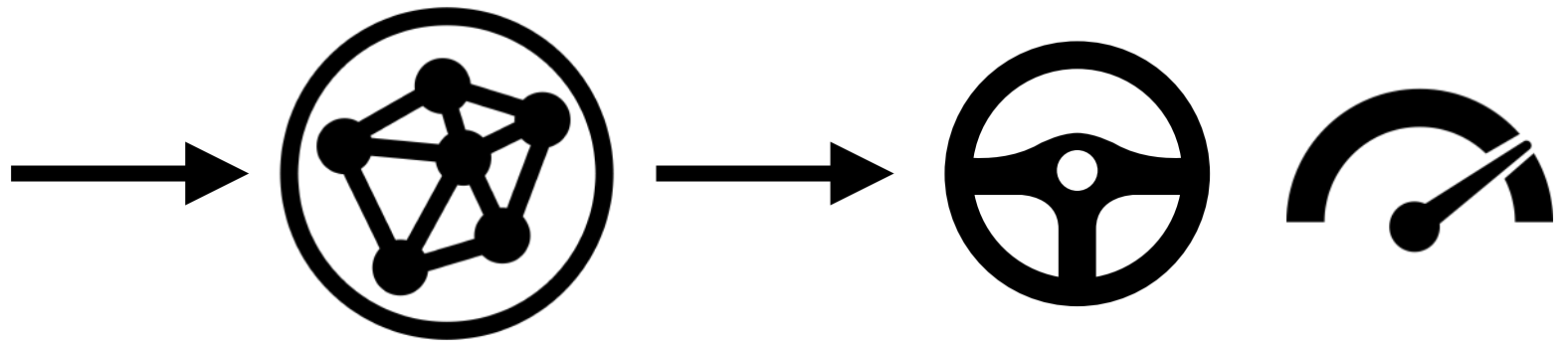


Mixed-reality framework

○ End-to-end ADS execution



Mixed feed



Lane-keeping
ADAS
(DNN)

Outputs

Mixed-reality framework

○ End-to-end ADS execution

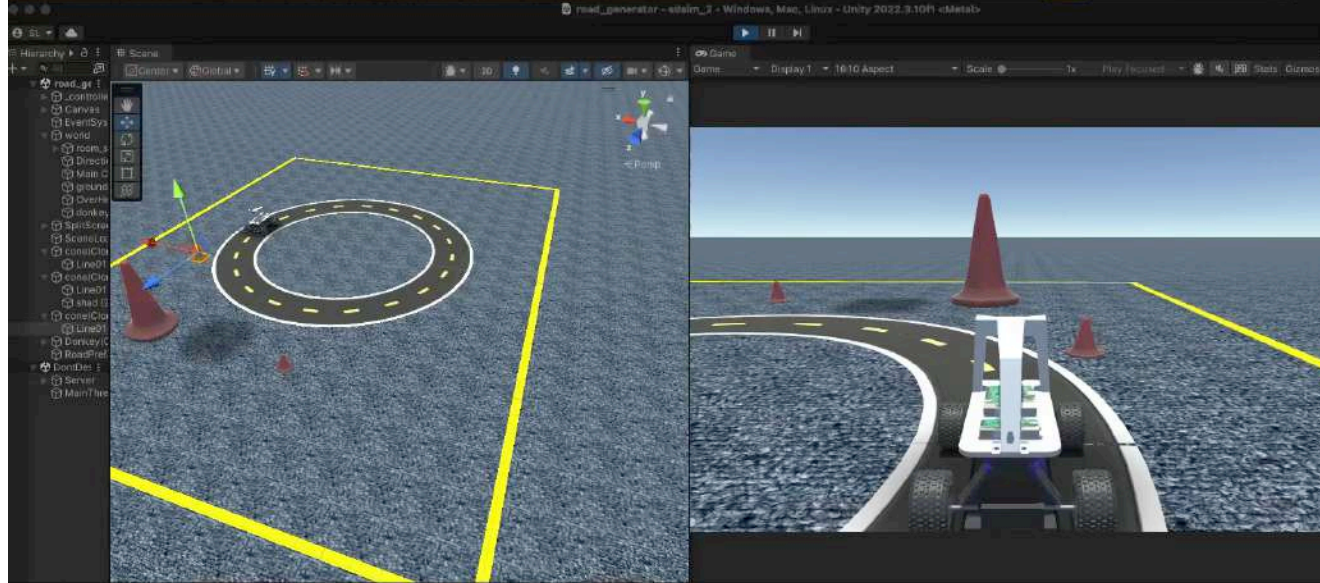
Real world



Mixed-reality



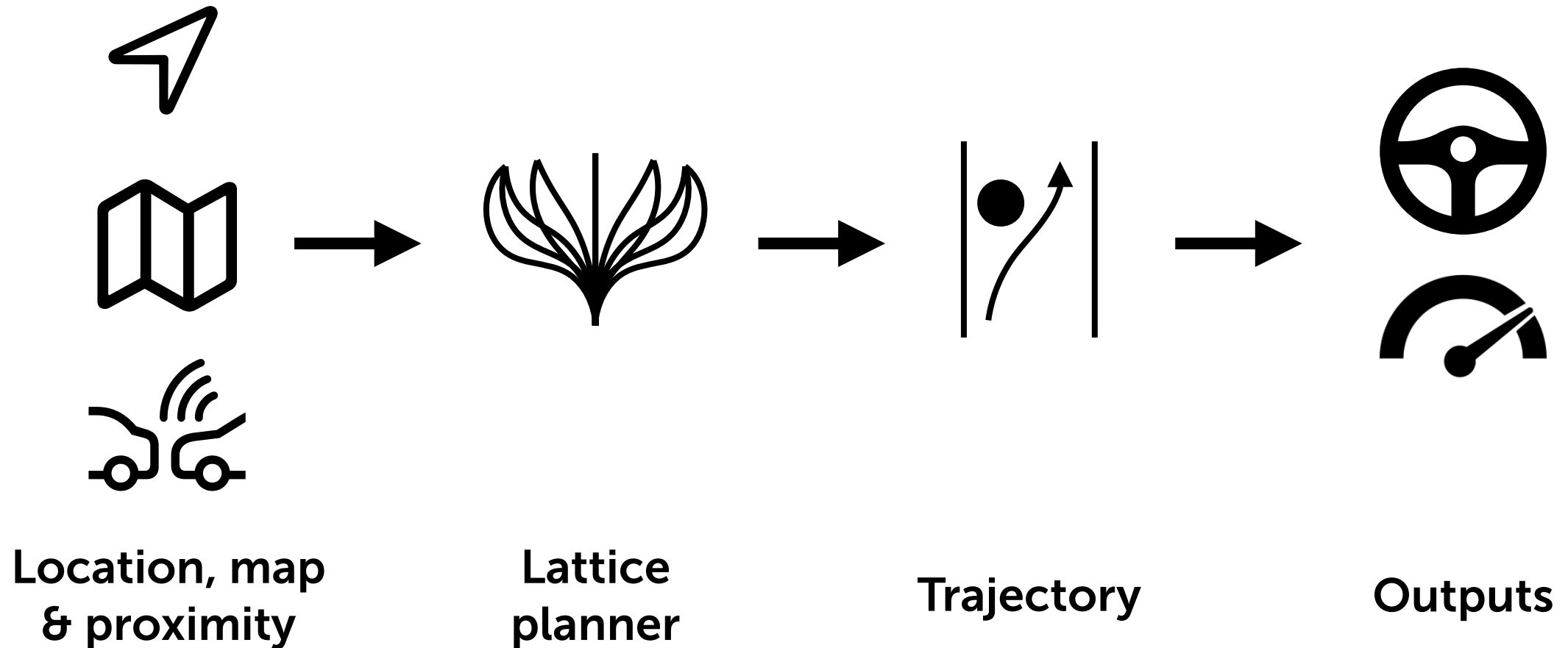
Simulation



Simulation
(FOV)

Mixed-reality framework

○ Path-planning ADS execution



Mixed-reality framework

○ + Real software stack



Mixed-reality framework

○ Path-planning ADS execution



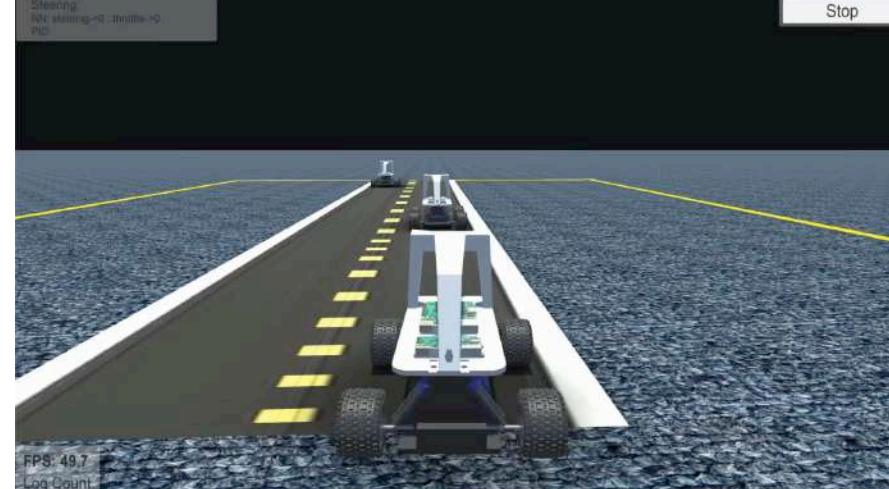
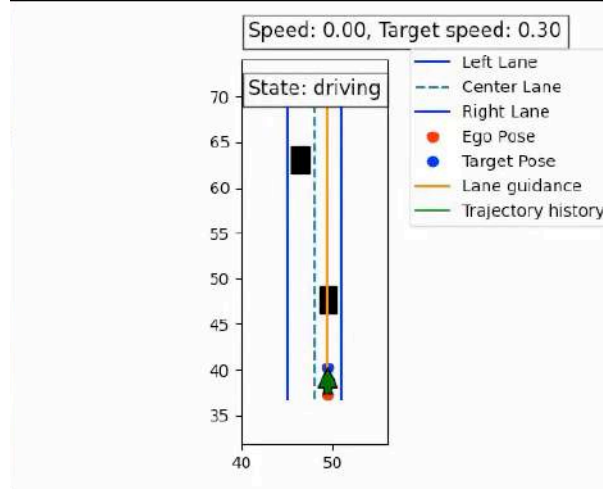
Real world



Mixed-reality



Path planning



Simulation (FOV)

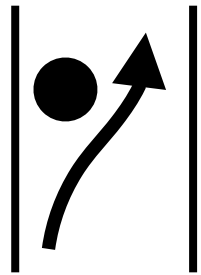
Mixed-reality framework

○ + Autoware
Planning

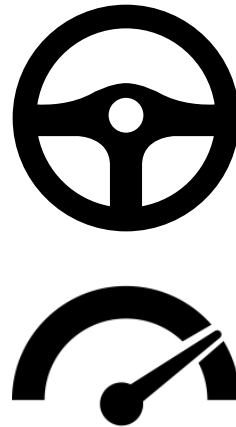


Demonstration

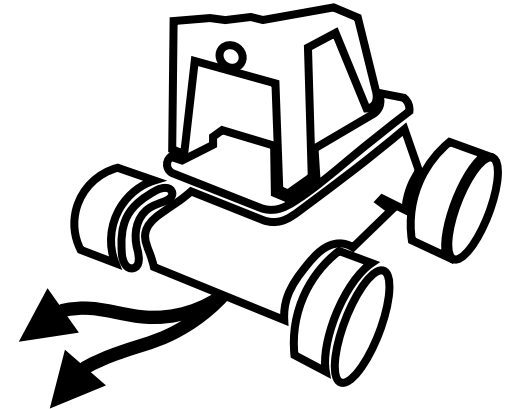
○ A small sim2real gap demonstration



Trajectory



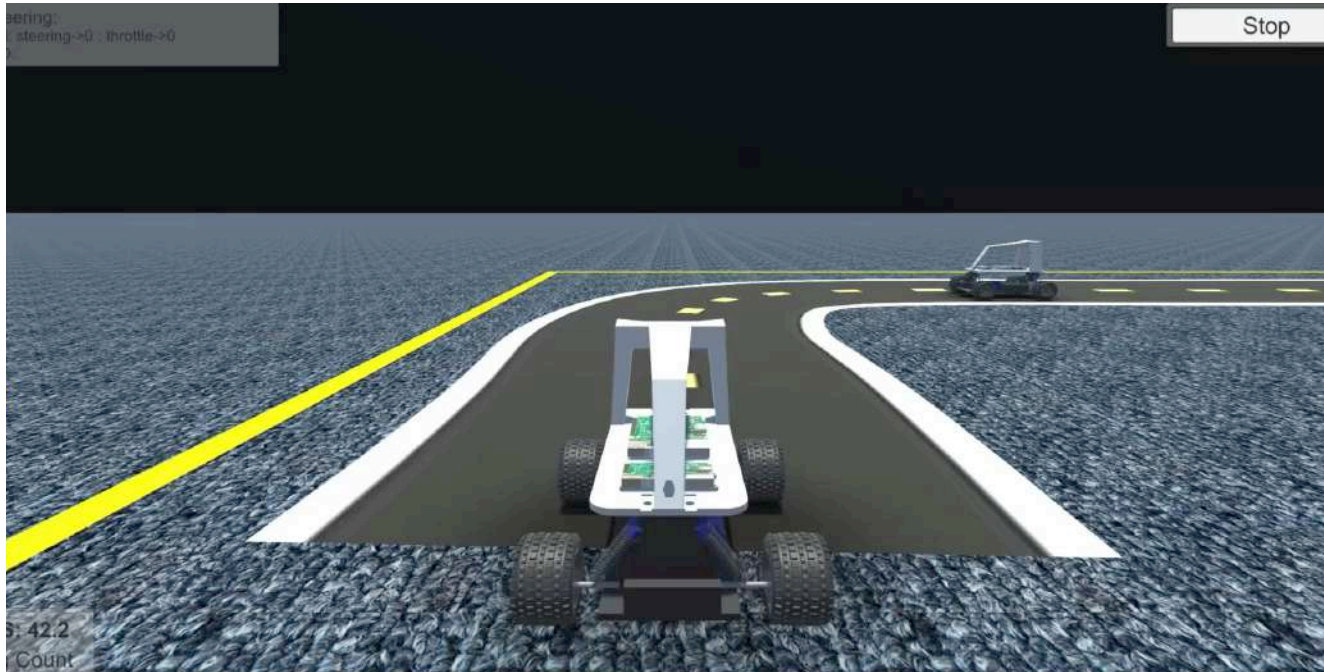
Outputs



Sim actuation
 \neq
Real actuation

Demonstration

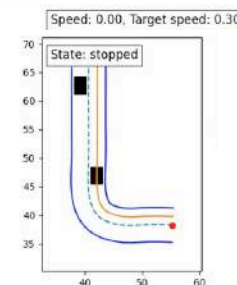
○ Simulation only



Safe distance:
0.5m

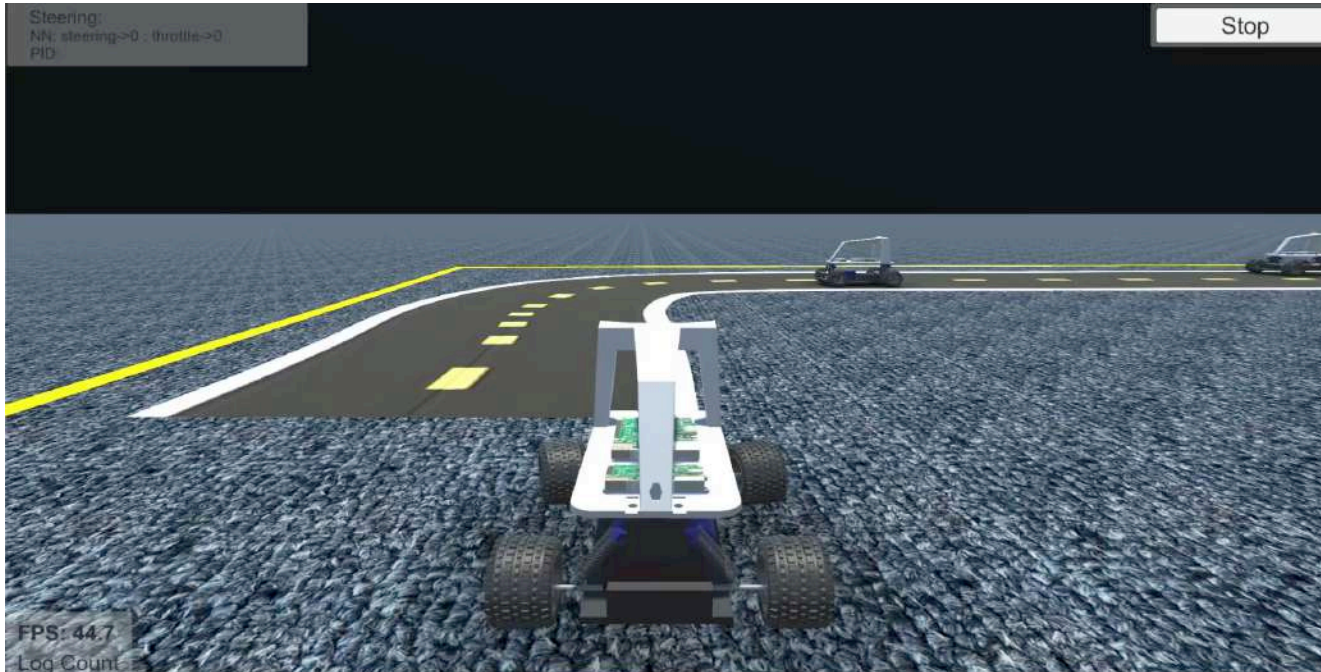


Target speed:
0.3m/s



Demonstration

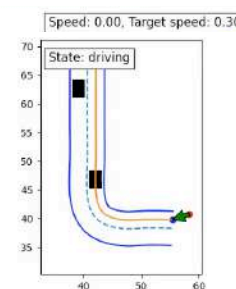
○ Mixed-reality execution



Safe distance:
0.5m

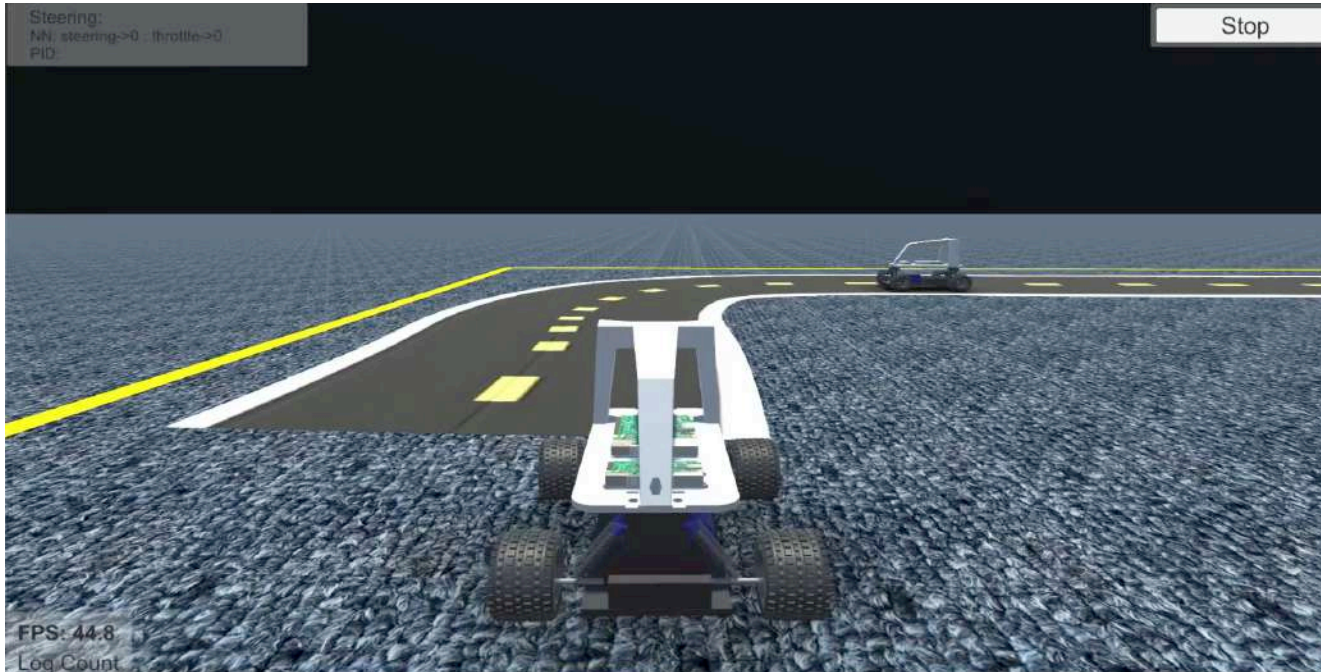


Target speed:
0.3m/s



Demonstration

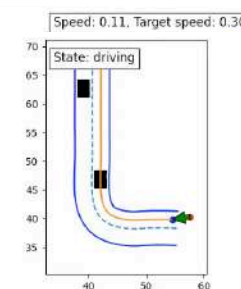
○ Rectified mixed-reality execution



Safe distance:
0.7m

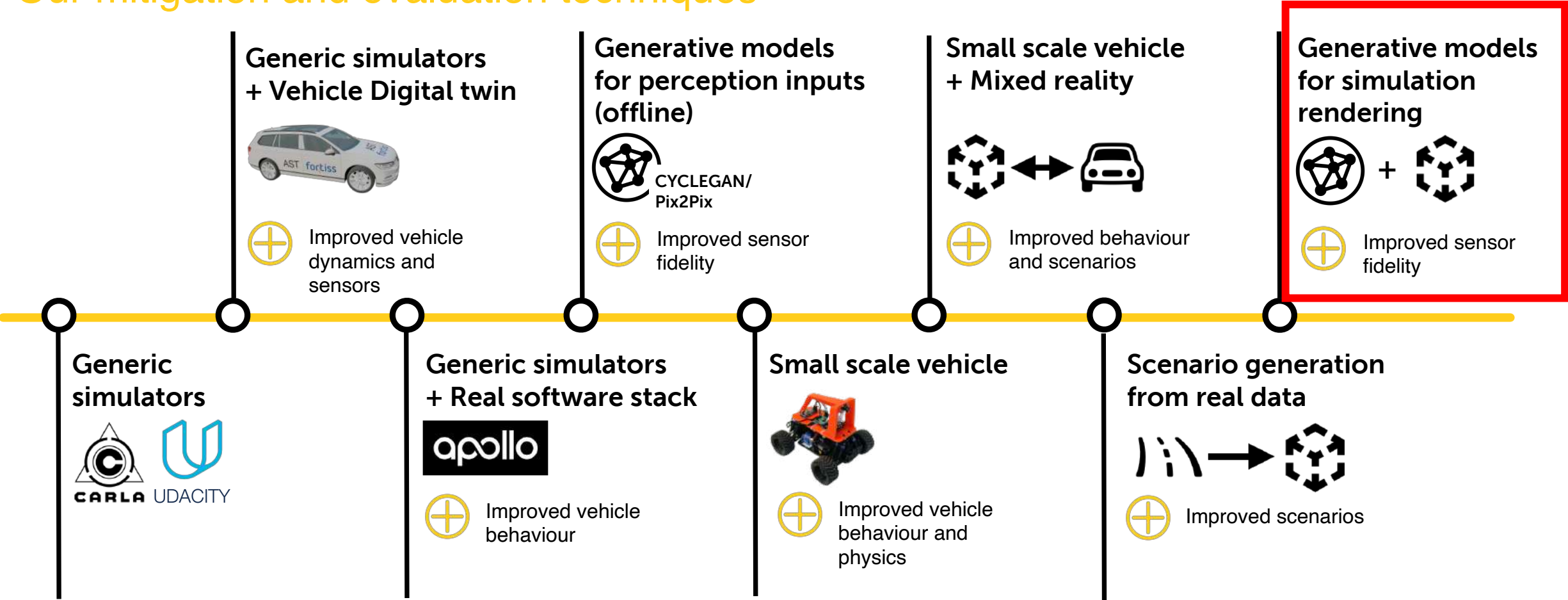


Target speed:
0.3m/s



Reality Gap

Our mitigation and evaluation techniques



ADAS requires extensive coverage of the ODD



From regulations to implementation

Existing Standards and Regulations

- ISO/PAS 21448 Safety of the Intended Function (SOTIF)
- UN Regulation No 157 (2021/389)
- ISO 34505 “Scenery Elements (Section 9)” and “Environmental Conditions (Section 10)”

Operational Design Domain (ODD)

- roadway types
- geographic area
- environmental conditions (weather as well as day/night time)

Diffusion Models

Used for Training Set Augmentation

Augmentation: **Lightning Strikes**



Input Image



Instruction-edited



Inpainting



Inpainting with
Refining

Augmentation: **Autumn Season**



Input Image



Instruction-edited



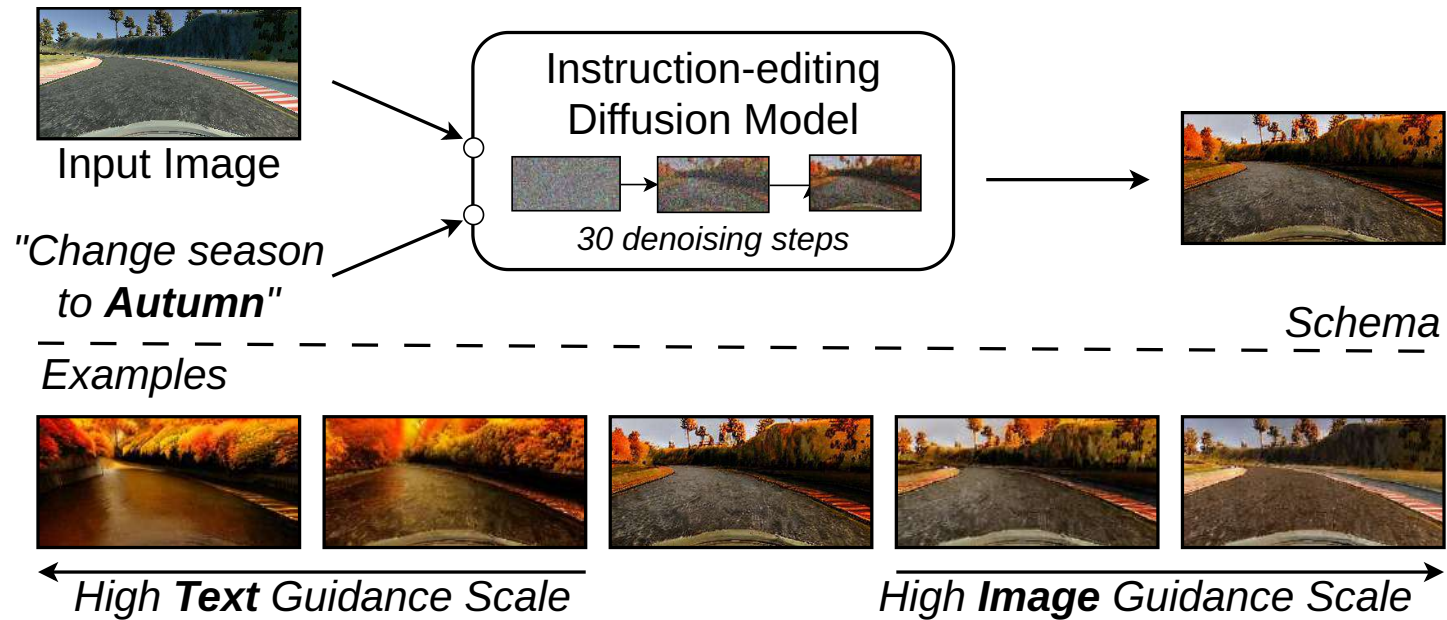
Inpainting



Inpainting with
Refining

Instruction-editing

Prompt: Textual



Enhancing ADS Testing with Driving Simulators and Generative AI

Simulators with Generative AI (naïve integration)

InstructPix2Pix



Diversity



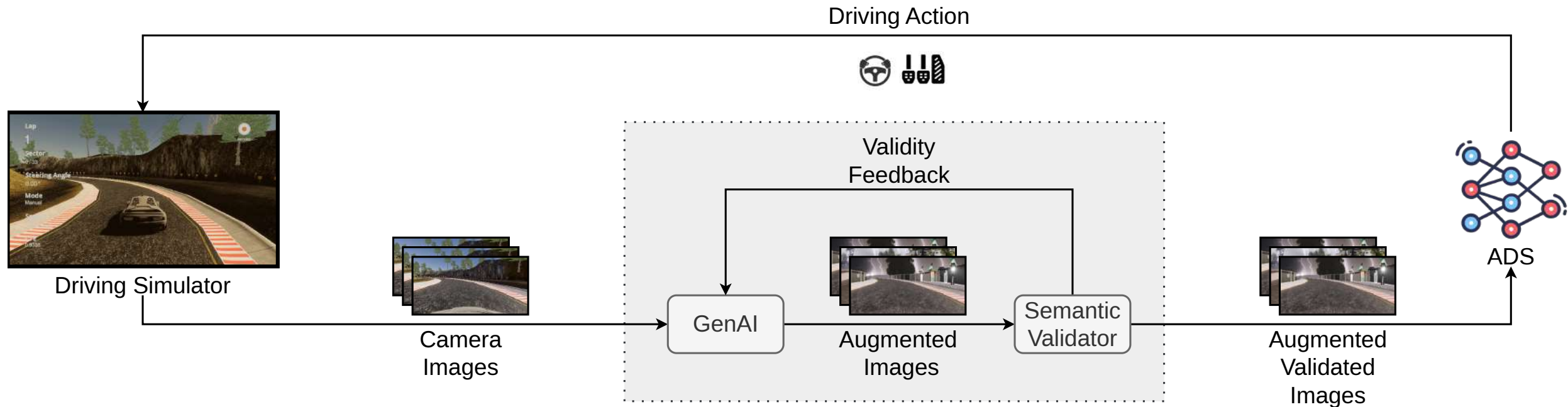
Temporal Consistency



Efficiency **+11-20X** overhead

Enhancing ADS Testing with Driving Simulators and Generative AI

Simulators with Generative AI



Enhancing ADS Testing with Driving Simulators and Generative AI

Simulators with Generative AI (knowledge distillation)

InstructPix2Pix with Knowledge Distillation



Diversity



Temporal Consistency



Efficiency **+0.02X** overhead

Baresi, Hu, Stocco, Tonella.

Efficient Domain Augmentation for Autonomous Driving Testing Using Diffusion Models.

47th IEEE/ACM International Conference on Software Engineering (ICSE) 2025





Egypt



Brazil



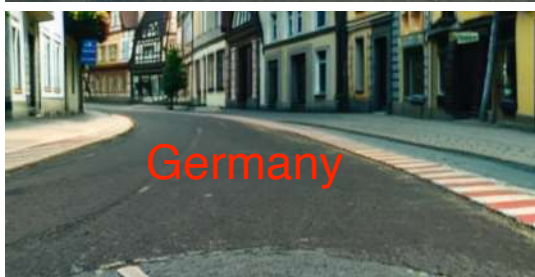
Australia



Argentina



Canada



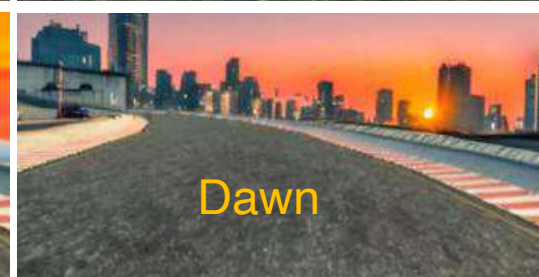
Germany



Evening



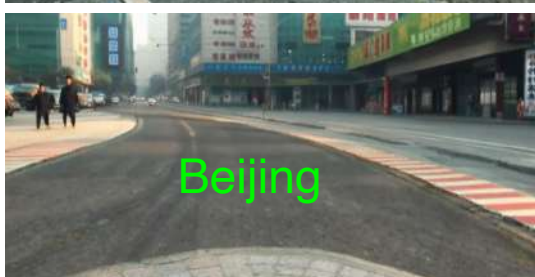
Sunset



Dawn



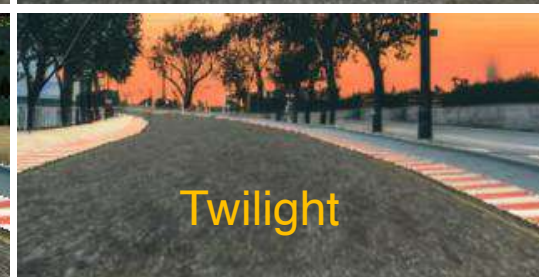
England



Beijing



Morning



Twilight



Autumn



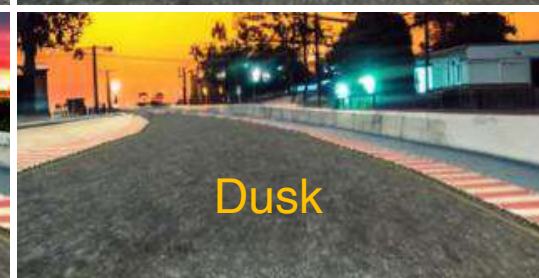
Berlin



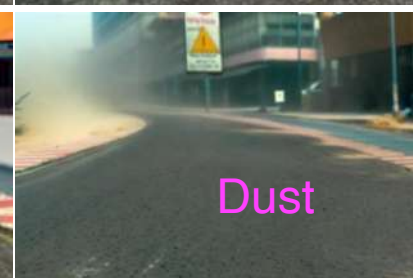
Night



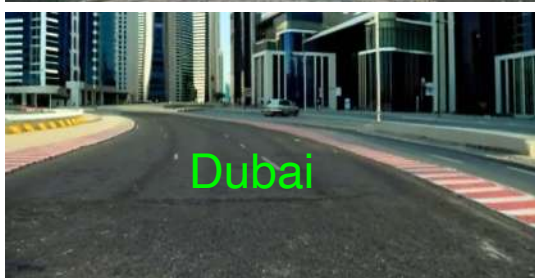
Sunrise



Dusk



Dust



Dubai



Forest



Blizzard



Snow



Foggy

Takeaways

ORIG
ODD

I

NEW
ODD



Behaviour
Metrics



Diffusion
Models

1

Diffusion models effectively tackle domain generation for ADS testing

2

They complement simulator testing, uncovering failures in areas previously considered error-free

3

Knowledge distillation is key to achieving high simulation efficiency

Baresi, Hu, Stocco, Tonella.

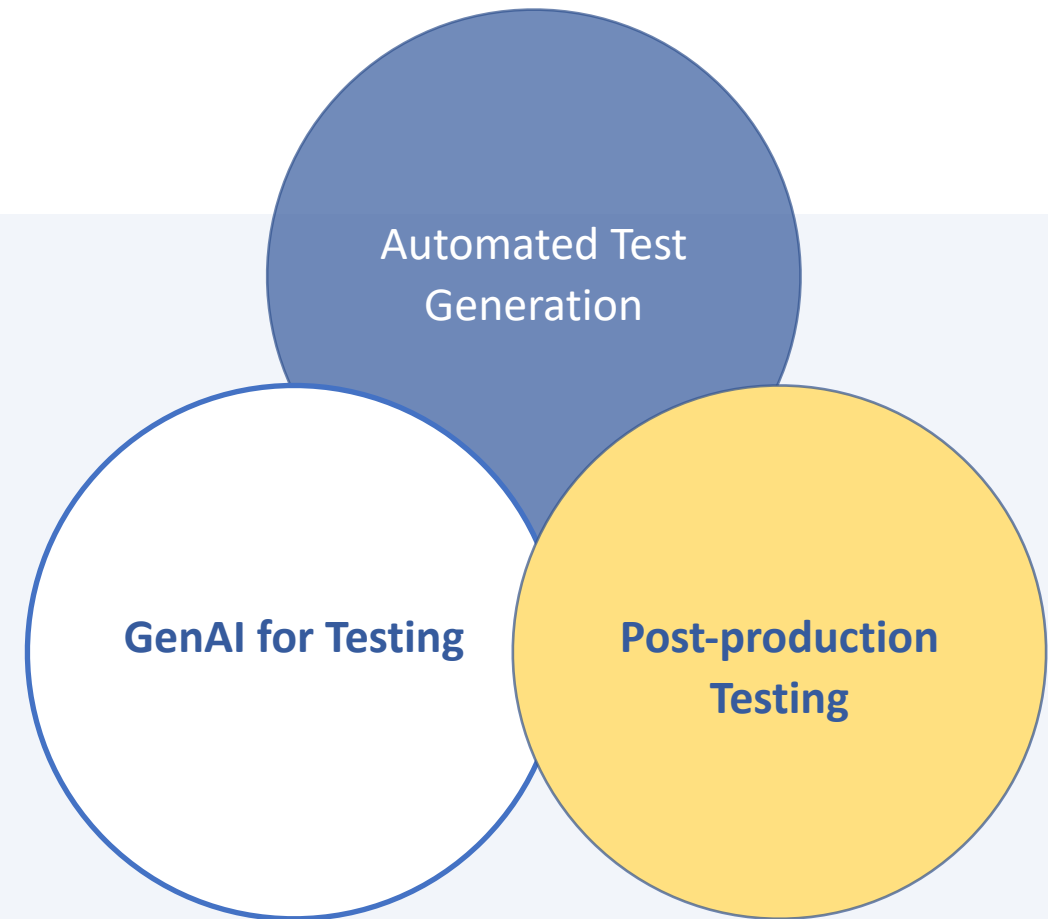
Efficient Domain Augmentation for Autonomous Driving Testing Using Diffusion Models.

47th IEEE/ACM International Conference on Software Engineering (ICSE) 2025

Automated Software Testing

Main research topics

- **Automated Test Generation**
How can we automatically generate complex scenario-based tests efficiently and effectively?
- **GenAI for Testing**
How can we leverage generative adversarial techniques, uncertainty quantification and conformal predictions, explainable AI for testing CPS
- **Post-production Testing**
How to ensure a high dependability of deep neural network driven-cyber-physical systems (CPS) in production?



Post-production Testing

Real-time monitoring of deployed ADS



ADS & ADAS

- End-to-end DNNs (level 2)
- Full AD stacks



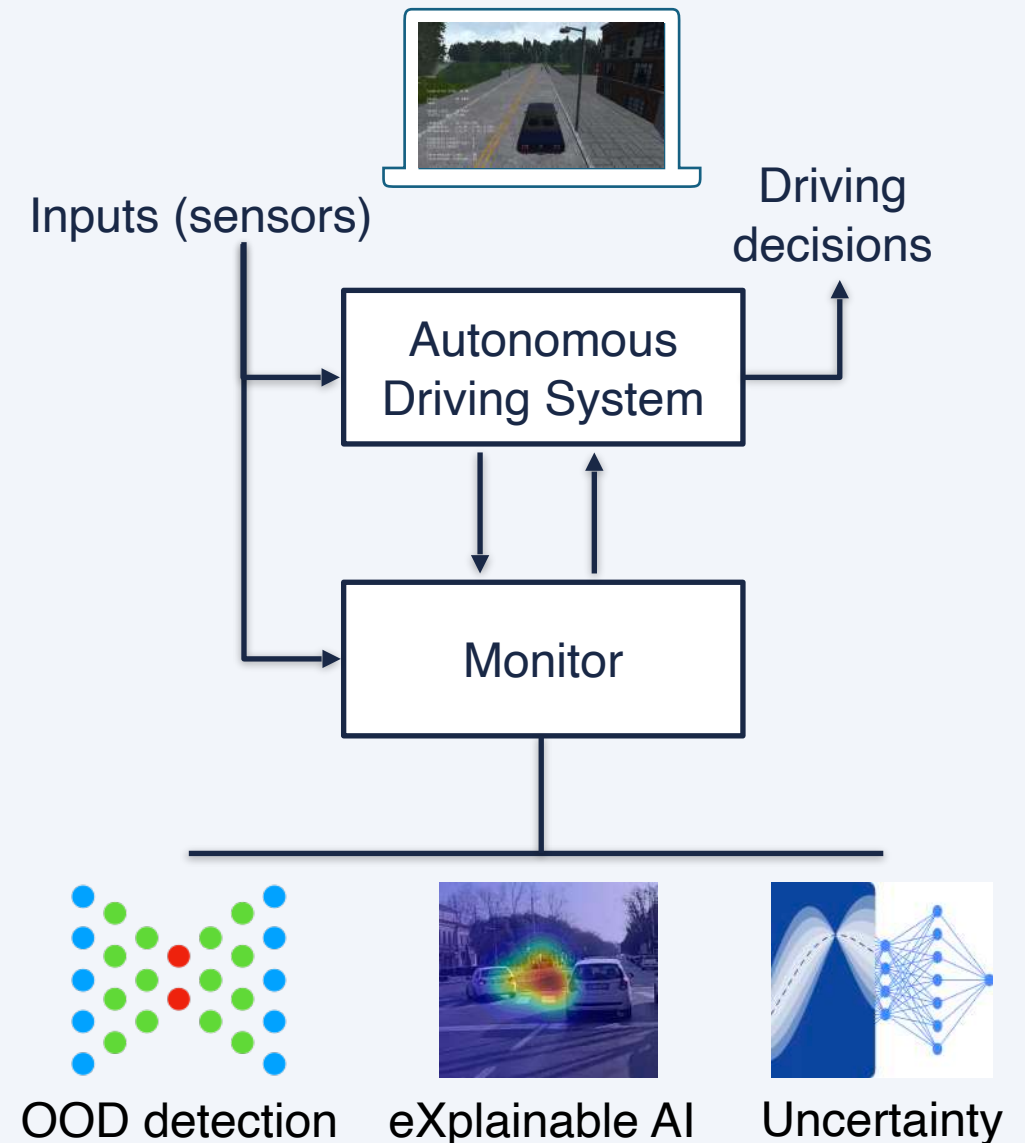
Real-time Monitoring

Observe System Under Test at runtime



Trustworthy ADS

Alert the driver if system is not to be trusted or activate fallback procedures



Stocco, Weiss, Calzana, Tonella.
Misbehaviour Prediction for Autonomous Driving Systems.
In Proceedings of ICSE 2020.

Vielen Dank!



fortiss ©2025

Diese Präsentation wurde von fortiss erstellt. Sie ist ausschließlich für Präsentationszwecke bestimmt und streng vertraulich zu behandeln. Die Weitergabe der Präsentation an unsere Partner beinhaltet keine Übertragung von Eigentums- oder Nutzungsrechten. Eine Weitergabe an Dritte ist nicht gestattet.